The Regional Multi-Agent Simulator (RegMAS): an open-source spatially explicit model to assess the impact of agricultural policies

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The Regional Multi-Agent Simulator (RegMAS): an open-source spatially explicit model to assess the impact of agricultural policies

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Abstract

RegMAS (Regional Multi Agent Simulator) is an open-source spatially explicit multi-agent model framework specifically designed for long-term simulations of the effects of policies on agricultural systems. Using iterated conventional optimisation problems as agents' behavioural rules, it allows for a bidirectional integration between geophysical and social models where spatially-distributed characteristics are taken into account in the programming problem of the optimising agents. With RegMAS it is possible to simulate the local specific response to a given policy (or scenario), where policies, together with macro and regional characteristics, are read into the program in specially formatted spreadsheets and standard GIS files.

The paper presents the model logic and structure and describes its functioning by applying it to a case-study, where RegMAS results are compared with conventional agent-based modelling to demonstrate the advantages of spatial explicitness. The simulation refers to the impact of the recent "Health Check" of the CAP on farm structures, income and land use in a hilly area of a central Italian region (Marche).

Key words:

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Agent-Based Modelling, Mathematical Programming, Explicit Spatial Analysis, Common Agricultural Policy

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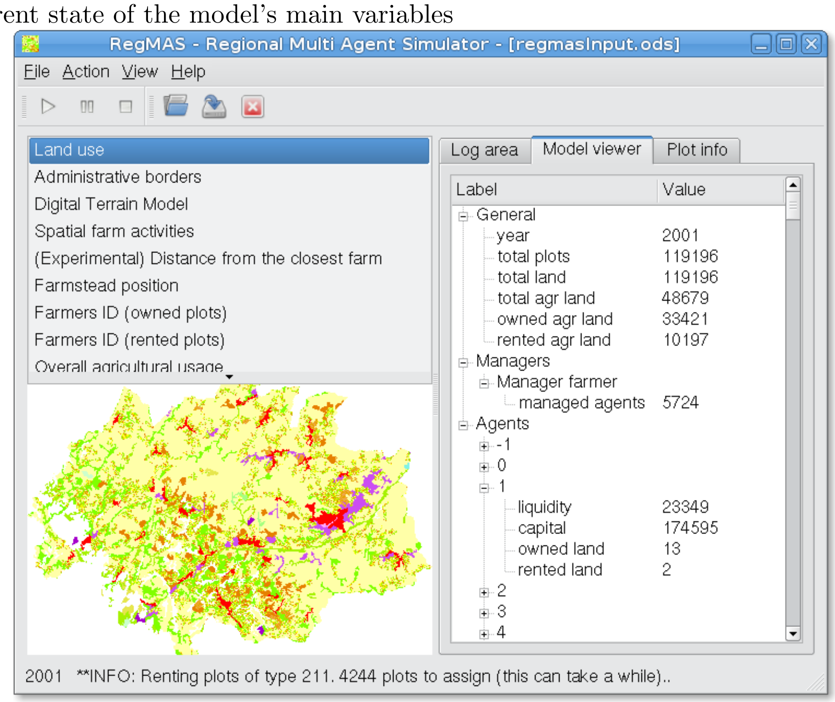
1. Introduction

Farm-based modelling approaches seem better suited than partial or general equilibrium models (like ESIM, FAPRI/AGMEMOD or GTAP) to analyse the impact of changes in external conditions (for instance in policy regime) on agricultural activity and performance (Heckelei & Britz, 2005). In particular, mathematical programming, and more specifically Positive Mathematical Programming (PMP) models, are widely used in agricultural policy analysis (Paris, 1991; Arfini, 2000). However, by modelling representative agents, they miss the interaction between heterogeneous farmers, while this aspect is explicitly considered in so-called Agent-Based models (ABMs).

RegMAS (Regional Multi Agent Simulator) is an open-source spatially explicit multi-agent model framework, developed in C++ language specifically designed for long-term simulations of the effects of agricultural policies on farm structures, income, land use, etc.. More specifically, RegMAS conceives agricultural systems as complex evolving systems made of a set of heterogeneous"agents" (mostly farmers) whose behaviour is generated by a conventional profit-maximisation problem in the form of a Mixed-Integer linear Programming (MIP) problem. Farmers compete in the land-market and use the "new" rented land (together with investments and other purchased inputs) to increase their competitiveness.

Noticeably, however, the original feature of RegMAS is that farmers behaviour explicitly and realistically takes space into account. The spatial dimension is initialised from real land-use data, using satellite information, and plots are explicitly modelled within the agents' problem as individual resources with spatial information organised in different layers (e.g. land typology, altimetry, environmental constraints, etc..) (Figure 1). This approach allows very detailed analysis along the spatial dimension, as farmers' decisions can be based on individual plot properties and farmers' activity can admit spatial interaction (e.g., through the impact of distance on costs and land renting) and can be evaluated from a multidimensional perspective, for example by including the environmental point of view (land abandonment, for instance).

Figure 1: RegMAS user interface showing the available layers, the case-study region and the current state of the model's main variables



In this paper we thus describe the RegMAS modelling framework and demonstrate its potential by applying it to evaluating the impact of the recent EU Common Agricultural Policy (CAP) reform known as "Health Check" on a real Italian territory. The application emphasizes the effects of such policy change on different farm types to show how the model is able to take into account both structural and spatial heterogeneity (for instance, distinguishing between small and large farms but also between plain and mountainous farming). This case study aims at demonstrating the advantages and applicability of the spatial explicit modelling in RegMAS.

Section 2 describes the methodological approach underlying RegMAS. After a short introduction of agent-based modelling applied to agricultural systems (2.1), the section focuses on the two key modelling issues, modelling farmers behaviour (2.2) and making space explicit (2.3), and then describe how the model is structured and solved (2.4). The case-study is then presented in section 3 and results of this application discussed in section 4 where the model is applied to alternative scenarios and sensitivity analysis is performed in order to better verify and validate model logic and functioning with special reference to spatial explicitness. Section 5 finally concludes.

2. The logic behind RegMAS

2.1. Overview

Agent-Based Models (ABMs) within the specific agricultural context were pioneered by Balmann (1997) with the Agricultural Policy Simulator (AgriPoliS) model. ABMs allow representing economic and social systems as the result of individually-acting agents. When applied to agriculture, they can simulate, at the micro-level, the behaviour of individual farmers, without the need of aggregating them in "representative" agents, and then generate the macro (aggregate) evidence. Furthermore, ABMs can catch the iterations of the heterogeneous farms when competing over common finite resources, e.g. land.

Parker (2003) and Boero (2006) review several ABMs involving land use changes in various scientific areas, including agricultural economics, natural resource management, and urban planning. This section shortly describes how RegMAS borrows many concepts from previous ABMs (as AgriPoliS), *in primis* the adoption of a profit-maximisation algorithm to model farmers behaviours.

In AgriPoliS agents are mainly farmers[1] whose objective is the maximisation of household income[2]. To achieve this objective, farmers solve a MIP problem that is, in some aspects, farmer-specific. Beside solving this linear programming problem, farmers can operate in the land market by deciding to rent or to release agricultural plots. Any farmer in the model is a real farmer taken from farm-level datasets (in Europe, the Farm Accountancy Data Network, FADN) and explicitly associated to a spatial location. Space (i.e. location) is important in the model for two basic reasons: it influences transport costs (through distance) and makes farmers interact each other, by competing for the same bordering land plots. Also due to privacy-protection regulations, however, it is not usually possible to have access to the real farm localisation. Therefore, space can not be modelled according to the real land

[1]Other agents perform specific tasks, such as managing land market or coordinating product markets.

[2]Nonetheless, throughout the paper for simplicity we use term "profit" to express the objective of maximisation though in agricultural context it could be more appropriate to use "farm gross revenue" as objective function or, if household activities are also included, "household income".

coverage but only randomly distributing farmers over a virtual region. Most recent applications of AgriPoliS allow model initialisation from real land-use data, using satellite information (Piorr et al., 2009). However soil remains homogeneous within the same quality class.

A detailed description of AgriPoliS can be found in Happe et al. (2006) and in Kellermann et al. (2007). Sahrbacher et al. (2005) describes AgriPoliS implementation over several case-study regions and Lobianco (2007) presents an adaptation of AgriPoliS to the Mediterranean agriculture.

2.2. RegMAS: modelling farmers behaviour

RegMAS uses Mixed Integer linear Programming (MIP) techniques to derive farmers behaviours, with profit maximisation as objective function. There is no real alternative to mathematical programming in modelling farm behaviour over such disaggregation of activities and heterogeneity. Any parametric estimation of a more flexible technology would be, in fact, unaffordable.[3] It is also true that, within mathematical programming techniques, valid alternative solutions to conventional linear programming do exist in modelling individual behaviour: multiple goal programming, recursive multiperiod programming, dynamic programming, etc.. (Hazell & Norton, 1986; Romero & Rehman, 2003). Here, however, a simple linear profit maximisation problem is adopted not only because it is the prevalent approach in agricultural policy modelling (Ellis et al., 1991; Happe et al., 2008). It also has the advantage of flexibility, as it can account for the whole range of farm

[3] Paris (1991) and Arfini (2000) present an in-depth analytical description and a literature review of linear programming techniques applied to farm modelling, respectively.

activities, from growing specific crops to investing in new machinery or hiring new labour units. Moreover, it is computationally feasible within an agent-based contest where each agent has *its own* objective function and further computational effort is demanded by the spatial-explicit functioning of the model as illustrated below. A final advantage of the MIP is that the introduction of integer parameters allows scale effects to emerge in the model, thus letting farmers evolve their response and performance on the basis of their economic and physical size included land rental behaviour.[4]

Any farmer autonomously makes his own decisions by solving his own MIP problem:

$$
\begin{array}{lll}
\max_{x_i} & Y = \sum_{i=1}^{C+I} (GM_i * x_i) & \\
s.t. & & \\
& \sum_{i=1}^{C+I} a_{i,j} * x_i \leqslant b_j & \forall j = 1, ..., J \\
& x_i \geqslant 0 & \forall i = 1, ..., C+I \\
& x_i \in int & \forall i = C+1, ..., C+I
\end{array}
\tag{1}
$$

where:

[4]Further future developments of the present model can evidently concentrate the attention on more sophisticated, and perhaps realistic, representation of farmer behaviour. The computational costs of more behavioural complexity within a spatially explicit ABM, however, will still remain the limiting factor.

i	= activities index	Y	= profit
j	= resources index	GM_i	= gross margins
C	= continuous activities	b_j	= capacities (RHS)
I	= integer activities	$a_{i,j}$	= technical coefficients
J	= resource constraints	x_i	= production quantities (argument of the maximisation)

The resource and activity sets are open: the RegMAS user is free to include (or exclude) further individual activities and resources. In the current version, we implement within the model all typical activities and resources in running a farm, financial and labour activities included. While in specialised linear-programming models these activities can be very detailed, in ABMs the presence of different types of farmers, for any of which a specific programming problem has to be solved, makes the analysis limited to more aggregated activities.

Farmers maximise their profit any time they bid to rent a new land plot (2.3.2) in order to calculate the respective shadow price, or any time they plan a new investment, or decide the production levels using available resources and assets. The initial farm's endowment (financial assets, land endowment, machinery, animals. etc.) can be taken from real datasets (FADN data in the present case). In problem (1) these data (vector A in Figure 2) represent the right-hand-side terms of the constraining inequalities. Any farmer chooses from a list of activities. They can be divided in two categories: activities that generate costs and revenues within one year (B) and activities that generate results over multiple years (i.e., investments, C). Investments can only take integer values but a given asset is still available in different sizes, allowing scale-effects to emerge in the model (e.g., larger-size investments may have smaller unit costs or labour requirements).

To solve problem (1) farmers choose the quantities of the various activities (D) that maximise the objective function (E), i.e. profit. The gross margins of the various activities (F) are the parameters of the linear objective function, while the matrix of coefficients G links the activities (B+C) with their respective constraints (H).

According to this structure, RegMAS simulations can be run to assess how farmers adapt to changes in their environment. Such changes may concern either resource endowment (their constraints) or activity gross margins, and may be generated either endogenously, when they result from the model solving procedure (e.g., an investment decision or new rentable plots released by farms exiting the sector), or exogenously (e.g., changes of market prices or of policy support associated to a given activity). In addition, agents' performance can evolve over a simulation period on the basis of investments made in previous years also according to how farmers' finance is modelled and enters the MIP problem. This latter aspect requires a detailed and specific description.

2.2.1. Financial aspects

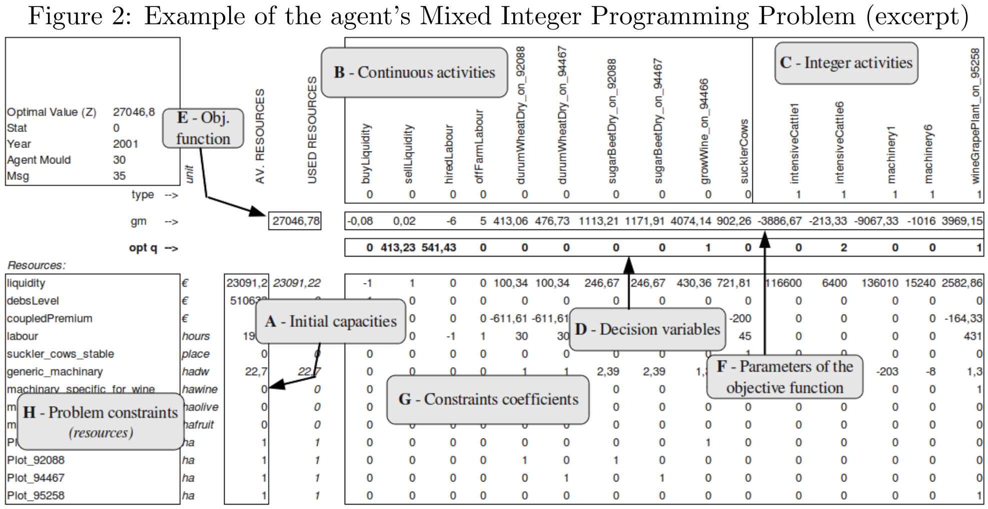
In RegMAS, investments require liquidity. To calculate the liquidity available to farmers at the beginning of year t, we sum the liquidity available at the beginning of year (t-1) to all revenues and costs occurred over year (t-1) and subtract the sunk costs to be paid before starting production in year t. Liquidity is thus calculated as follow:

$$
\begin{aligned}
liquidity_t \quad = \quad & liquidity_{t-1} + productionProfits_{t-1} + decPayments_{t-1} \\
& -withdrawals_{t-1} - \sum_{n=0}^{N} invCosts_{t-1,n} \\
& -sunkCosts_t \qquad (2)
\end{aligned}
$$

where:

($productionProfits$) comes from (t-1) MIP optimisation including coupled premiums and off-farm activities. ($decPayments$) expresses the $decoupled_{t-1}$ support received in year (t-1). ($\sum_{n=0}^{N} invCosts_{t-1,n}$) represents the total expenditure for investments made in year (t-1). ($sunkCosts$) are costs generated from previous choices, like multi-year rental costs or investment maintenance costs. ($withdrawals$) are the financial resources required by the farmer's household to support its own private expenditure and costs. They are calculated as a fixed portion of profit plus a minimum requirement level

Figure 2: Example of the agent's Mixed Integer Programming Problem (excerpt)



that depends on the farm size (measured in family Annual Work Units):

$$\begin{aligned} withdrawals &= perCapMinwithdrawalal * AWU \\ &\quad +max(0, profits * withdrawalalProfitShare) \end{aligned} \tag{3}$$

Within RegMAS, ($invCosts_t$) can be also covered borrowing money on the credit market (*loans*). A farmer can obtain loans on the credit market up to a maximum share of the total capital value (this maximum is currently 80%). Each year the farmer optimises the amount of money to be borrowed on the credit market given its financial situation and the exogenous cost of credit (i.e, the interest rate).

The capital endowment at the beginning of year t is thus calculated as the sum of liquidity and the current value of past investments:[5]

$$capital_t = liquidity_t + \sum_{i=0}^{I} investmentCurrentValue_{i,t} \tag{4}$$

with I is the number of own capital goods (assets). The real depreciation of different investment objects may depend from the characteristics of the investment itself, but in the current version of the model the investment value linearly decreases for all object types. Therefore, due to the presence of loans, (4) actually represents total capital as combination of debt and equity capital under the aforementioned constraint that the debt capital can never exceed 80%.

[5]Land is not included in this calculation as it is directly read from the farmers' data file and its endowment never depreciates.

2.3. RegMAS: making space explicit and real

As AgriPoliS, RegMAS has a spatial dimension, that is, it considers the spatial heterogeneity in such a way that, for example, the model can associate a different rental price to each plot and, thus, can investigate possible land abandonment even when land cultivation is *on average* profitable. Differently from AgriPoliS, however, this spatial dimension is fully explicit, in the sense that, not only plots are initialised from real cartographic data, but they are also explicitly modelled in the decision matrix as individual resources, without the need of aggregating them in soil classes.

2.3.1. Region initialisation

Before running the simulation, the model must fix the environment where the simulation will be generated. This environment includes different dimensions: the legislative (subsidies, legal constraints...), the biophysical (agronomic and technical coefficients) and, finally, the economic dimension (factor and product prices). Then, individual farmers can be created, positioned in the modelled space and granted with the tools and resources they need to operate (e.g. land, machinery, financial resources...).

Unfortunately, detailed data on all the individual farms (micro data) within a given region all are often unknown (sometimes for privacy reasons) while aggregate (macro) data (for instance, size distribution) are usually available (e.g. from Census). Therefore, to re-create the simulation region, the model uses sample farms, for which detailed data are available (in the present case, farms belonging to the FADN), then weighed with a scaling coefficient in a such a way that the difference between the aggregate figures of the simulated region and of the real region is minimised (Eq. 5):[6]

$$\min_{UC_n \geqslant 0} \quad \sum_{k=1}^{K} \left(\frac{\sum_{n=1}^{N} (FADN_{n,k} * UC_n)}{REGIO_k} - 1 \right)^2 \tag{5}$$

where:

Indices:	Variables:
$n = \{1, ..., N\}$ Individual farms	$FADN_{n,k}$= FADN data
$k = \{1, ..., K\}$ Macro characteristics	$REGIO_k$= Regional aggregate data
	UC_n= "upscaling" coefficient
	(argument of the minimisation)

2.3.2. Land allocation, land market and transport costs

After region initialisation, an obvious problem when dealing with spatially explicit agent based models concerns the localisation of agents and of their spatial objects. As there is already an informative layer, consisting of the real land use (the Corine Land Cover database), we need to make the model consistent with this layer, by placing farms over it. Firstly, farms are assigned a random location selecting a plot compatible with their activities, starting from the less common. The simple idea is that "rare" land uses have the precedence over more common land uses to minimise distance between such plots and the farmsteads. Hence, if a farm has, for example, both plots with fruit plantings and plots with arable crops, the farmstead position will correspond to the fruit plantings. Subsequently, plots are assigned to the

[6]This procedure is called "upscaling" and it is well documented in Kellermann et al. (2007), while a practical implementation is discussed in Sahrbacher et al. (2005).

closest farm that has still an un-assigned capacity for that specific soil type, giving precedence to owned plots in comparison to rented ones.

Such land allocation is not, in fact, an optimisation algorithm as plots are not assigned to farms in such a way that the total *plots_X_farmsteads* distance is minimised. After all, the real world itself is far from being an optimal land allocation across farms, as physical boundaries and hereditary rules sometimes split the farm land endowment in several scattered plots often generating a fairly fragmented allocation.

This initial land allocation across farms, however, is not definitive. During model simulation farmers can bid to rent new plots. Different assumptions on modelling land market can be made within an ABM (Kellermann et al., 2008). In the present case, we assume a rental market made up of fixed-term contracts whose duration is randomly chosen within a fixed interval. In practice, RegMAS doesn't allow direct *farmer-to-farmer* renting contracts, as farmers can only rent land from an anonymous intermediate agent that operates in the land market collecting plots released by farms exiting the business, in addition to the initial pool of rentable plots. This agent makes all these plots available to farmers through a bid where only the farm offering the highest price eventually rents the plot.

Any farmer associates a shadow price to any rentable plot and when asked to bid he offers a fraction of this shadow price to take into account both fixed and variable transaction costs and overheads. The shadow price for any rentable plot is simply calculated performing two MIP optimisation problems, with and without the plot, and calculating the difference between the two profits (see section 2.2).

In existing ABMs, like AgriPoliS, land heterogeneity only consists in different soil types; therefore, plots are homogeneous within the same soil type and farmers are guaranteed to place the highest bid for any certain soil type on the closest plot. This allows these models to speed up the algorithm code of the land rental market. RegMAS, on the contrary, works with real land-use data therefore plots are heterogeneous also within soil types thus making such algorithms very computationally demanding (all bid from any farmer on any plots should be collected). To limit the computational complexity but also to add more realism to land market functioning, therefore, RegMAS offers the option to restrict the bidding process to the farmers operating within a given distance from the rentable plots; the exact number of bidders (that is, the spatial range over which any farmer can rent land) is a parameter calibrated according to the transport costs: the higher the transport costs, the lower the likelihood that a given farm may offer a successful bid (thus, the smaller the range over which he can operate). This is a critical form through which space enters the model: distance and costs associated to it affects the capacity of a farm to rent new land and, thus, to afford a better economic performance. Symmetrically, heterogeneity of land allows to take into account local plot characteristics in forming plot rental prices (and, eventually, in their rental status).

Once the rentable plot is assigned to the farm that won the bid a new rental contract is established for a random (and, then, fixed) period (the RegMAS user can establish the duration) and the plot, eventually associated to its spatial objects, enters the farmer's optimisation problem as a new resource.

2.3.3. The spatial dimension in the optimisation problem

Due to such spatial explicitness, the farmer maximisation problem 1 changes as it takes into account plots as individual resources and each spatial activity is specified for each plot. The optimisation problem becomes:

$$
\begin{array}{lrcll}
max_{x_i} & Y & = & \sum_{i=1}^{N+S*P} (GM_i * x_i) & \\
\quad s.t. & & & & \\
& \sum_{i=1}^{N+S*P} a_{i,j} * x_i & \leqslant & b_j & \forall j = 1, ..., R+P \\
& b_j & = & 1 & \forall j = R+1, ..., R+P \\
& a_{i,j} & = & 1 & \forall \quad i > N \vee i = N + (j-R) \\
& x_i & \geqslant & 0 & \forall i = 1, ..., N + S * P
\end{array}
\tag{6}
$$

where:

i	= activities index	Y	= profit
j	= resources index	GM_i	= gross margins
N	= non-spatial activities	$a_{i,j}$	= technical coefficients
S	= spatial activities	b_j	= capacities (RHS)
R	= constraining resources	x_i	= production quantities
P	= individual plots		(argument of the maximisation)

If the number of plots available to a farmer increases, however, the problem matrices is expected to grow to a size hardly manageable even for modern calculators. Therefore, RegMAS follows a sort of "filtering" procedure that, before adding the activities to the matrix, checks for consistency of any activity with the plot land use and eventually with the presence of the necessary objects (an example could be that wine growing activity could be made only on suitable land with planted vineyards).[7] Despite the higher computational costs, using individual plots in the decision problem allows spatial activities to be evaluated by farmers on the basis of characteristics of their associated plot. This means that farmers can take account of transport costs associated to distance of a given plot from the farmstead and of plot's altitude (the hypothesis being that gross margins declines with altitude). This GIS-alike functionality allows a full linkage between the economic and the geophysical parts of the model.

Similar advantages arise on the output side: when the land use remains implicit in the matrix decision matrix (e.g. farmers are presented with the "agricultural_land" total resource rather than with each individual plots) the spatial location of production remain undefined.[8] When, on the contrary, the farm optimises a matrix with an *activity_X_plot* structure, the model can allocate the corresponding chosen activity to its associated plot.

2.4. RegMAS: model structure and solving

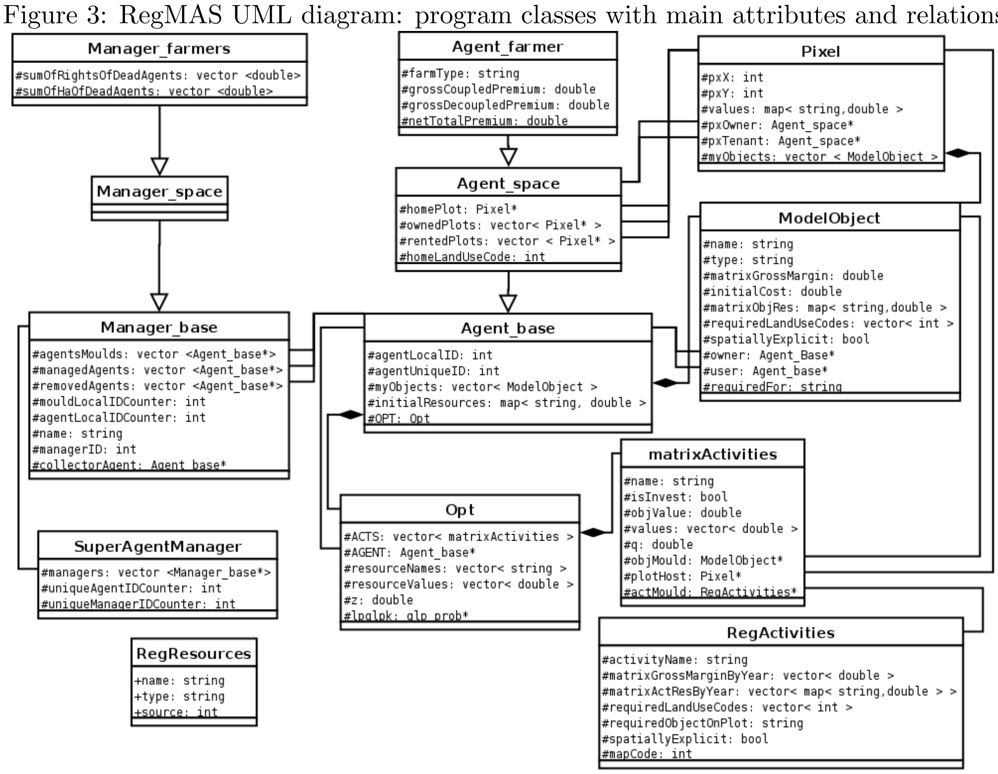
RegMAS has been designed from the ground up to explicitly consider farmers as one specific type among several possible types of agents. "Farmer" agents are derived from a more general type of "spatial" agents that is, in

[7]The Reference Manual has a pseudo-code that details the steps the model does to add activities to the MIP problem, available at `http://regmas.org/doc/referenceManual/html/classOpt.html`.

[8]Various algorithms could be used (*ex-post*) to assign production to a particular plot. One of them is discussed in Brady et al. (2009). It assumes that farmers, given a certain mix of production activities, try to spread them in the smallest possible number of fields, maximising their size. However, land is still considered fully homogeneous within the same soil type.

turn, derived from a "basic" type. Each agent type has its own "manager" agent that interacts with a "Super Agent Manager". The former is a sort of "agent-side" interface while the latter implements the same interface on the program "core-side". In this way, the model core does not need to "know" the agents internal logic. Figure 3 depicts the organisation of the model framework at the program level by providing the RegMAS Unified Modelling Language (UML) diagram with the main classes and their relations.

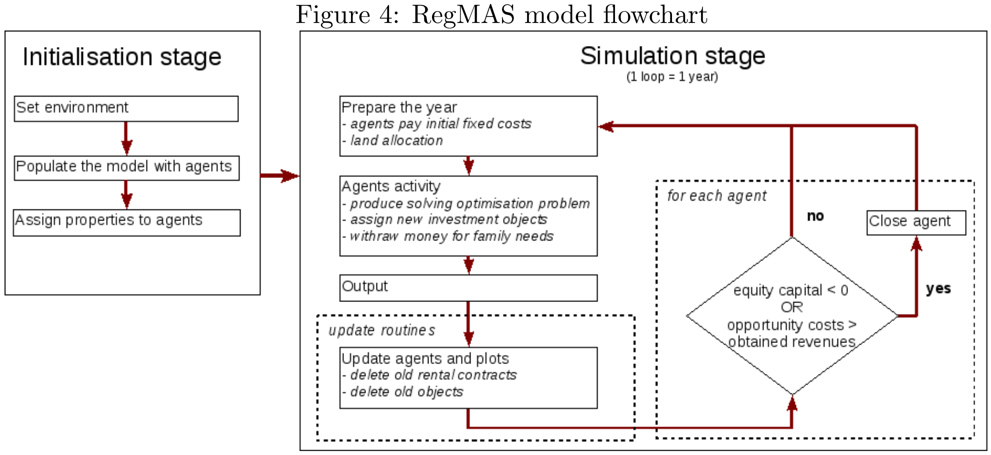
Figure 3: RegMAS UML diagram: program classes with main attributes and relations



While this approach allows for rapid development of different agent types (as only specific characteristics need to be modelled), the current RegMAS mostly focuses on the specific domain of agriculture, thus farmer agents, but it has also the potential to emphasize connections with other social systems, for instance "urban" agents.[9]

Figure 4 summarizes the main logical steps of the model. As typical in ABMs, the initialisation stage is critical because the relevant characteristics of the "real world" must be incorporated in the model (see also section 2.3.1), the agents must be entered and they must be endowed with the relevant objects, in our case production factors. After initialisation the model can proceed into the simulation stage; simulation is organised in loops: any year land is allocated to farmers; thereafter, they can activate production activities by solving their optimisation problem. Before proceeding to the next year, the model updates all the relevant (exogenous) variables and select those farmers that can continue the activity while others exit the business whenever their equity capital goes to zero or off-farm opportunity costs exceed farm profit.

Figure 4: RegMAS model flowchart



To run simulations, RegMAS solves a MIP problem like (6) for any in-

[9]Analysing the Italian Corine Land Cover data between 1990 and 2000, Lobianco (2006) highlights that the largest change in agricultural land use, beside the shift to other agricultural uses, concerns reallocation to urban uses, revealing a competition between these two land destinations.

dividual farm and in several steps during each simulated period, resulting in thousand computations for each period, though the “filtering” procedure illustrated above substantially reduces the matrix activity size. It follows that the speed of the solving algorithm becomes a critical factor.

In fact, RegMAS uses external libraries to speed-up the solving algorithm. RegMAS class **Opt** is responsible to establish the direction of the objective function (in our case, a maximisation), the set of bounds, objective coefficients and constraint coefficients. Then, the problem “object” is solved calling an external Dynamically Linked Library (DLL). RegMAS uses the open-source GNU Linear Programming Kit (GLPK) (Makhorin, 2007) that firstly applies a two-stage revised simplex method for continuous solutions and then a Branch & Bound method in case of integer optimisation.

From the computational point of view this latter methodology is particularly helpful. In fact, MIP problems are more computationally demanding than LP (Linear Programming) problems. However, the Branch & Bound method, by partitioning the maximisation problem in sub-problems whose upper and lower possible solutions are reciprocally compared, allows for an efficient search of the optimal solution over a much smaller domain.[10]

3. Model verification and validation: a case-study application

To assess whether the depicted model works correctly and is able to properly and plausibly reproduce the real world, we apply RegMAS to a case-study area. As mentioned, RegMAS is mostly designed to analyse how het-

[10]Sub-problems with an upper bound lower than any other sub-problem lower bound are automatically eliminated from the search.

erogeneous agents (farmers) operating over a territory respond to changes in the external environment (scenarios). Changes in agricultural policy regime evidently represent well-suited applications.

Unfortunately, it is not possible to validate the model on the basis of some real historical observations that we can try to reproduce by running model simulations. On the one hand, RegMAS is fairly data demanding (census, FADN, detailed land coverage data) and, as mentioned, such requirements can not be met, for whatever territory, in any of the previous policy reform whose impact could be analysed within RegMAS. On the other hand, the only detailed territorial data (still at municipality level, at maximum) are only available for few years (2001 the most recent) and are needed to calibrate the MIP coefficients, as explained below. Nonetheless, we can firstly adopt a case-study approach to verify if the model works correctly in reproducing the largely expected impacts of policy reforms. Then, the major features of RegMAS can be validated through sensitivity analysis, that is, by comparing its simulation results with results obtained when such original features (especially in terms of spatial modelling) are dropped thus reverting to existing conventional ABMs.

For such purposes, we choose a case-study area that: (a) provides all required data and informations, (b) is small enough to restrain computational burden but, at the same time, (c) still heterogeneous enough to show how the model is able to link farmers' response and local territorial characteristics.

Therefore, for our simulations we select a hilly region of central Italy, Colli Esini (in the middle of Marche region), including 24 LAU2 municipalities and approximately 50,000 UAA, hosting in 2001 around 6000 farms. As emerges from its Land Use map shown in Figure 1,[11] its main characteristic is the presence of two different areas: a well-endowed and fairly homogeneous agricultural area at East closer to the urban part; a more heterogeneous, mixed agro-forestry area on the South-West, closer to mountains.

This area has been thus selected both because of his representativeness of Italian agriculture and because of the different forms of agricultural heterogeneity it presents and that make the model potentials fully exploited and explored. Marche region presents an agriculture which assumes many of the typical characteristics of Italian agriculture. In particular, the remarkable heterogeneity in production conditions and in production activities, ranging from plain and very productive areas to marginal mountainous farming, from undifferentiated productions (cereals) to high-quality typical productions (wine), from labour-extensive (grassland) to labour-intensive activities (horticulture). Within this context, the selected region "Colli Esini") seems fully representative: it is a small enough area to make model simulations computationally affordable but still maintaining all the abovementioned heterogeneity with plots ranging from fertile plain to marginal mountainous areas, from coastal to inner parts of the region, from pasture land to intensive high-quality vineyards.

To make the application more realistic, MIP technical coefficients have been derived either from recent literature values or from the respective FADN data; prices come from market data. Both coefficients and prices, however, required some calibration. By using real observations at the maximum ter-

[11] The map is part of the Corine Land Cover and it follows its conventional colours: yellow indicates agricultural areas, red urbanised areas and green natural areas.

ritorial disaggregation (municipality data in 2001), it is possible, in fact, to calibrate such information in order to make the model closely reproduce the observed macro-evidence, in particular to reproduce the aggregate (at municipality level) land allocation across productions.

3.1. Policy scenarios

Beside the selection of the area, the case-study also requires the definition of proper (policy) scenarios on which model simulations can be ran. Due to the relevant expected implications on land use, here we implement the recent reforms of the European Common Agricultural Policy (CAP) and, in particular, the decoupling of support.[12] Agricultural policies of most OECD countries underwent major regime changes over the last decade, with a substantial migration from market intervention and support coupled to production to decoupled farm-specific payments sometimes based on historical entitlements; the 2003 Fischler Reform is somehow exemplary of this general propensity in re-designing agricultural policies (Baffes & de Gorter, 2005; Antón & Sckokai, 2006).

Essentially, the Fischler 2003 CAP Reform (whose implementation started in 2005), assigns EU farmers a direct support (the Single Farm Payment, SFP) exclusively linked to historical payments (the 2001-2003 "reference period") and no longer associated with actual productions.[13] This reform has been further extended with the so-called Health Check of the CAP in 2008

[12]Most policies can be implemented in RegMAS just operating on the input files; nonetheless, the open-source nature of RegMAS allows the user an easy implementation also of policies that require a code revision.

[13]This is, in fact, the implementation of the 2003 Reform in Italy, as other countries actually opted for a regionalised flat payment.

(EUCOM, 2008). We thus run simulations starting from 2001, in order to include the reference period. Over 2001-2003 years, the model "collects" the coupled subsidies received by each farm, then automatically calculates the Single Farm Payment (SFP) due to any different farmer and finally assigns the SFP to farmers.

Therefore, for each farmer the model keeps track of three vectors: **dRights**, **dYears** and **dHa**. **dRights** are the average (over the reference period) entitlements that a farmer "owns" for the decoupled payment, differentiated by specific production activity. **dHa** are the average hectares that have generated the entitlements for the specific activity. Finally, **dYears** are the years for which these averages have been calculated. Using an "activity-specific flag" to indicate the reference period, every year the model updates the entitlements for each agent and each activity:

$$\begin{aligned} dRights_t &= (dRight_{t-1} * dYears_{t-1} + newRight_t)/(dYears_{t-1} + 1) \\ dHa_t &= (dHa_{t-1} * dYears_{t-1} + newHa_t)/(dYears_{t-1} + 1) \\ dYears_t &= dYears_{t-1} + 1 \end{aligned} \tag{7}$$

where ($newRight$) is the coupled premium obtained for that year by the farmer on the specific activity but only if the "activity flag" is in "registration" mode. Consequently, different products may have different reference periods, even not continuous.

In assigning the entitlements to each farmer in terms of SFP, RegMAS can actually distinguish between historical SFP (Eq. 8) and area-based SFP

(Eq. 9):

$$dPayment = \sum_{i=1}^{N+S} dRights_i * dRateCoef_i \tag{8}$$

$$dPayment = (\sum_{i=1}^{N+S} \sum_{y=1}^{A} dRights_{i,y} * dRateCoef_i / \sum_{i=1}^{N+S} \sum_{y=1}^{A} dHa_{i,y}) * \sum_{i=1}^{N+S} dHa_i \tag{9}$$

where $N{+}S$ are all the activities; $(dRateCoef_i)$ counts for eventual partial decoupling and A is the number of agents in the model. Note that in both historical and area-based payments, for a given year/activity, the farmer can still benefit from a mix of coupled and decoupled premiums. This farm-based modelling approach also allows for a detailed implementation of the further policy instruments introduced with the 2003 CAP reform and, in particular, of modulation.

On this basis, two policy scenarios have been defined:

Decoupling scenario (dec)

Historical SFP starts in 2005 (as this is the case in Italy, in fact) and the modulation on payments over 5000 euros rises from 3% in 2005 to 5% in 2007. Most payments are fully decoupled but some coupled ("quality") premiums remain (for durum wheat and *ex* art. 69 of the reform). This scenario approximates the actual implementation of the 2003 Fischler CAP Reform in Italy, including the national decisions in terms of decoupling options and art. 69.

Health Check scenario (hc)

The *hc* scenario corresponds to the *dec* scenario till 2008, but from 2009 onward it includes the decisions taken under the Health Check of the CAP agreed in November 2008 (EUCOM, 2008):

Modulation becomes stronger starting from 2009 and following the path reported in Table 1, while a minimum payment limit is introduced (payments below 250 euros are totally dropped);

Set aside - the mandatory minimum share (10%) is abolished from 2009;

Regionalisation - from 2010 the SFP calculation follows the area-based implementation (also known as "regionalisation") as in equation (9). The redistribution of the subsidies, however, excludes farmers without entitlements;[14]

Full decoupling - since Italy has already opted for full decoupling in 2003, the novelty only concerns the decoupling of the specific durum wheat payment (40 euros per ha) starting from 2010, on the base of the 2005-2008 reference period. The other "quality" coupled payments *ex* art. 69 (now, *ex* art. 68), however, are maintained.

[14]Though voluntary according to the Health Check final decisions, we assume that Italy opt for regionalisation starting from 2010.

Table 1: Modulation levels (in %) (*Health Check* scenario)

total farm payment (euros)	2008	2009	2010	2011	2012-2015
0 - 250[a]	0	100	100	100	100
250 - 5.000	0	0	0	0	0
5.000 - 100.000	5	7	9	11	13
100.000 - 200.000	5	10	12	14	16
200.000 - 300.000	5	13	15	17	19
> 300.000	5	16	18	20	22

[a] Payments over 250 euros are not affected by this modulation threshold.

4. Model verification: scenarios' results

Table 2 presents the model simulation results obtained running the *dec* and *hc* scenarios on the selected region from 2001 to 2015.[15] On the one hand, the number of farms seems only marginally influenced passing from *dec* to *hc*, as the drop in the 2008-2015 period is similar in the two cases (20.9% and 21.2%, respectively).[16] Farm number decline is one of the expected outcome of decoupling and the slightly larger decline observed under the *hc* scenario can be thus attributed to the slight further decoupling implied by the Health Check. On the other hand, the difference between the two scenarios becomes more evident focusing on farm size. Smaller farms seem more negatively influenced by the *hc* scenario and this is the expected outcome of the introduction of a minimum payment limit, i.e., of the suppression of small payments (<250 euros). As a matter of fact, these small payments represent only 0.68% of the total support (in 2008). However on

[15] Simulations have been conducted with Version 1.3 of RegMAS software. Readers can replicate them downloading RegMAS at `http://www.regmas.org`.

[16] Projections are presented starting from 2008 which it is the last year in which the two scenarios are equal.

small farms (<3 hectares) these small payments actually represent a much larger proportion of total CAP support (22.36%). The impact on local agriculture of this threshold, therefore, is neither trivial nor negligible.

Due to the larger modulation the number of larger farms increases much less in the *hc* case thus re-equilibrating the impact between medium and large size classes. At the same time, the net farm profit, i.e. not computing the CAP support, significantly improves under the *hc* scenario evidently due to the larger "freedom to farm" resulting from the abolition of the mandatory set aside and from full decoupling of durum wheat support (Antón & Sckokai, 2006).

The Health Check is often associated to even more intensive farming than *dec* scenario due to the possibility of cropping the former set aside land and to a stronger market orientation induced by further decoupling. Thus, this scenario also demands more labour to be subtracted from off-farm activities. This explains why, eventually, the impact of *hc* on household income, this being the sum of farm profit and income from off-farm activities, is almost negligible compared to the *dec* scenario.

Some of these effects of *hc* compared to the 2003 CAP Reform can be also attributed to the presumably more drastic novelty of the Health Check, that is, regionalisation of the SFP which is expected to generate a significant redistributional effect among farmers. Comparing the two scenarios on 2015 and considering the whole amount of subsidies (remaining production coupled payments plus SFP), we observe less farms that "loose" than farms that "win" money is smaller (46.43% vs. 51.31%). This explains why the average per year loss (1146.18 euros) is higher than the average gain (647.35 euros).

Nonetheless, due to the small average size of farms, only some exceptional cases loose or gain more than 5000 euros, while the large majority (92.4%) remains within the ±2000 euros range and 47.24% within the 500 euros range. Therefore, as expected, the model confirms that regionalisation does imply reallocation of support across farms but also that such effect is limited due the quite homogeneous and small size of farms themselves.

Though, as mentioned, it is not possible to validate the model on real-historical data, it is still interesting to assess model consistency by comparing its aggregate (macro) results with macro historical trends. In particular, if we consider the whole simulation period (2001-2015), RegMAS results indicate, on the selected area, a yearly 1,78% decline of the number of farms and a 0.20% decline of the UAA. This abandonment rate is fully comparable with what observed in Italy over the period 1990-2003 (2.32%). Looking at a more disaggregated territorial level, statistical data for the Marche region indicates a yearly decline of 2,67% in the number of farms and 0,26% in the UAA over the period 2000-2007. This limited difference can be ascribed to the fact that our study-area actually represents a "strong" agricultural territory compared to the average characteristics of the whole Marche Region.

4.1. Spatial effects

Table 3 summarises land use within the region in 2015 under the two scenarios. We use a conservative coefficient to establish altitude influence on the gross margin (2% loss each 100 meters); nevertheless, we observe that most abandoned plots, that is either vacant or uncultivated plots, concentrate in the hilly and mountainous part of the region (see also Figure 6). An important role in favouring abandonment in this part of the region is played

Table 2: Main simulation results: comparison of the two scenarios in 2015

	dec_2015	hc_2015	% var dec 2008–2015	% var hc 2008–2015	% var 2015 hc–dec
number of farms (n)	4,304	4,288	-20.9	-21.2	-0.4
- *small farms - [0-3] ha*	405	355	-73.9	-77.2	-12.4
- *middle size farms - [4-15] ha*	3,004	3,092	-2.4	0.4	2.9
- *large farms - [>16] ha*	895	824	10.4	1.6	-7.9
avg. size (UAA ha/farm)	10.97	11.01	23.5	24.0	0.3
exiting farms (n)	1420	1436			1.1
abandoned land (%)	3.25	3.27			0.5
farm profit (euros/farm)	10,981	11,386	12.1	16.2	3.7
- *including CAP aids*	16,068	16,202	15.7	16.6	0.8
income (euros/farm)	20,942	20,982	7.6	7.8	0.2
off-farm labour (h/farm)	975	956	-12.6	-14.3	-1.9
total agr. labour (AWU)	2,884	2,928	-12.5	-11.2	1.5

by its higher fragmentation due also to the larger presence of non-agricultural areas (forests, non-maintained grassy areas, etc.). Fragmentation increases the average distance among cultivated plots and, hence, transport costs are higher compared to the homogeneous agricultural area in the Eastern part of the region. In the South-Western part, land freed the by small farms that exit the agricultural activity may be too far to be economically advantageous for remaining farms, thus leading to land abandonment.

The comparison between the two scenarios, however, does not show any remarkable impact in this respect. Abandonment rate is almost the same in the two cases, though it slightly increases under the *hc* in the mountainous areas. After all, further decoupling and the introduction of a minimum payment limit may induce more very small farms to exit the activity, thus releasing more land that remains unrented. This effect, however, is compensated and almost entirely offset by the slight increase of support in less productive area due to regionalisation.

Table 3: Abandoned land by altitude (2015)

	dec		hc		hc-dec
Altitude	ha	%ab. rate	ha	%ab. rate	% diff
0-200m	769	2,31	774	2,33	0,65
200-400m	679	5,00	678	4,99	-0,15
400-900m	135	7,51	139	7,73	2,96

4.2. Model validation: comparison with a "spaceless" RegMAS

Model simulations over the two scenarios show that, also considering the specific features of the area under study, the internal structure of RegMAS seems consistent with the real world as it generates those effects that are generally expected, in direction and magnitude, from the introduction of the *hc* measures. Nonetheless, these aggregate results could be obtained by a properly defined conventional ABM, as well. To validate the original features of the model, that is, in particular, to demonstrate the advantages of spatial explicit modelling, we need to assess which kind of additional information such features (i.e., spatial explicitness) can provide compared to conventional ABMs. To pursue this kind of validation we carry out sensitivity analysis by comparing RegMAS results with those obtained by a RegMAS model where spatial features are dropped.

Firstly, we run the model without spatial influence on costs and land renting, that is, no transport Costs (TC) and, at the opposite, with TC augmented two and ten times, respectively. Moreover, space influences performance and renting behaviour also in terms of altitude. As mentioned, in RegMAS a simple coefficient simulates the reduction of gross margin due to altitude (the altitudinal coefficient, AltC). Therefore, we also perform model simulations under alternative values of the gross margin reduction coefficient:

the gross margin declines with the altitude at 0%, 4% (double than standard 2%) and 20% (ten times), respectively. Results of this sensitivity analysis are reported in Table 4.[17] When the spatial dimension (that is, distance and TC) is skipped, farms loose their advantage on close plots and enter a greater competition for land renting. Such more competitive environment leads to a reduction of the number of active farms. The opposite happens when transport costs increase and, thus, space acts as a non-competitive factor: the number of farms increases. This latter effect disappears, however, when TC become too high: they negatively affect farmer profit in such a way that a larger land abandonment occurs. Therefore, TC have a direct negative influence on farm profit and income but, at the same time, this effect may be counterbalanced by the impact on land market. With lower TC farms save costs but have to face the higher competition for land, resulting in higher rental prices, especially for activities with lower gross margin and on which, evidently, TC variations have a larger impact in terms of economic convenience to continue production (i.e, pasture land).

RegMAS thus seems fully capable of representing this not trivial effect of space (through TC) on farm performance and behaviour. This capability is also confirmed by results obtained under alternative responses of gross margin to altitude. As the AltC coefficient is expressed as a proportion of gross margin, productions with higher gross margins (e.g., wine, fruits & veg, etc.) are expected to be, in absolute terms, more sensitive to AltC while for TC the opposite holds true. This expectation is confirmed by results if we compare the impact of AltC variation on arable crops cultivated on dry land

[17]Analogous results can be obtained under scenario *dec*; results are available on request.

and on irrigable land (where gross margin is expected to be higher).

Another difference with TC is that AltC affects farm performance in a univocal way: if AltC decreases, performance improves in hilly and mountainous farming; the opposite occurs when AltC increases. This affects the number of active farms and, as a consequence, land abandonment. Table 5 reports the abandonment rates under the alternative AltC values compared to the baseline *hc* scenario. Results show that the response of abandonment to AltC variations is relatively inelastic. While abandonment remains almost unaffected in plain areas regardless AltC, as obvious, a large impact in hilly and mountainous areas can be observed only when the reduction of gross margin with altitude becomes very intense (20% loss any 100 meters).

Table 4: Sensitivity analysis on transport costs and gross margin reduction with altitude (% difference with respect to the *hc* scenario in 2015)

	noTC	2xTC	10xTC	noAltC	2xAltC	10xAltC
N farms	- 6.3	+ 1.9	- 6.9	+ 2.7	- 1.5	- 16.2
Total income	+ 0.7	- 2.3	- 34.7	+ 2.1	- 1.0	- 21.0
Rental prices:						
- *arable_dry*	+ 22.7	- 20.1	- 90.5	+ 4.6	- 7.0	- 47.9
- *arable_irrigable*	+ 7.9	- 1.2	- 25.6	+ 18.9	- 11.2	- 82.9
- *wine*	+ 3.2	- 3.4	- 19.4	+ 11.1	- 13.2	- 71.1
- *fruit*	- 1.1	- 7.7	- 17.9	+ 9.0	- 11.6	- 65.0
- *olive*	+ 5.6	+ 6.1	- 10.9	+ 6.3	- 7.3	- 66.5
- *pasture*	+ 110.6	- 49.7	- 98.8	+ 16.5	+ 1.3	- 76.2
Abandoned land	+ 15.3	+ 1.4	+ 892.4	- 8.3	+ 3.2	+ 134.7

Legend: noTC, 2xTC, 10xTC indicate no transport costs, double and ten times transport costs with respect to the *hc* scenario, respectively.
noAltC, 2xAltC, 3xAltC indicate no variation, double and ten times variation of gross margin with altitude compared to the original scenario (2% loss any 100m), respectively.

It may be argued that the capacity of RegMAS to take into account space (as distance/TC and altitude) in generating aggregate (macro) results can be also obtained in conventional ABMs where spatial features are actually

Table 5: The impact of AltC on abandonment rate in 2015 (%)

Altitude	Land abandonment rate			
	hc scenario	noAltC	2xAltC	10xAltC
0-200m	2.33	2.18	2.43	3.33
200-400m	4.99	4.38	5.06	15.19
400-900m	7.73	7.17	7.78	30.31

attributed to plots on a random basis rather than on the basis of the real land use coverage. Nonetheless, this latter solution would not be able to associate to this macro evidence the correct impact on land use (the micro level). To show this specific feature of RegMAS, a second sensitivity analysis consists in running the model on the same region but with all spatial information (land coverage and DTM, Digital Terrain Model, for altitude) randomly shuffled (*rand_space*). Figure 5 graphically compares the two cases: 5*(a)* shows land coverage and altimetric information as they enter RegMAS simulations with plots associated to the real land use; 5*(b)* shows how the area looks like when plots are assigned randomly. As evident, when the "real" spatial information is dropped, we miss the link between real local conditions and agents' behaviours. In particular, randomizing the space, we are unable to take into account those special and somehow extreme conditions of marginality that may induce farms to exit the activity and, therefore, to release or abandon land. Consequently, it should not surprise that the *rand_space* case also reports different aggregate (macro) results: a higher number of active farming at the end of the simulation (+3.73% in 2015) and a lower land abandonment rate (-12.4%).

Moreover, while in RegMAS results indicate a strong difference in land abandonment rate between plain and mountainous areas, in the *rand_space* case land abandonment remains homogeneously regardless altitude: in the 400-900 m altitude level the abandonment rate (2.97%) is only marginally greater than in the 200-400 m (2.85%) and 0-200 m (2.74%) levels. Figure 6 graphically displays agricultural land use (green) and land abandonment (red) in the area under the two cases: in RegMAS abandonment is associated to a condition of spatial marginality (6*(a)*) while this aspect is completely lacking when we miss spatial explicitness and assign plots on a random basis (6*(b)*). This further sensitivity analysis illustrates the major feature of RegMAS compared to conventional ABMs. It is able to generate macro evidence, as well, but starting from the real micro evidence, that is, the real use of land. As a consequence, the spatial features of the model do not only provide simulations of "real" land use change (with all environmental consequences) but also show how this change affects macro results themselves.

A final sensitivity analysis can be carried out on RegMAS looking for simulation robustness given its stochastic components. The stochastic nature of RegMAS derives from the following operations performed during model initialisation and simulation:

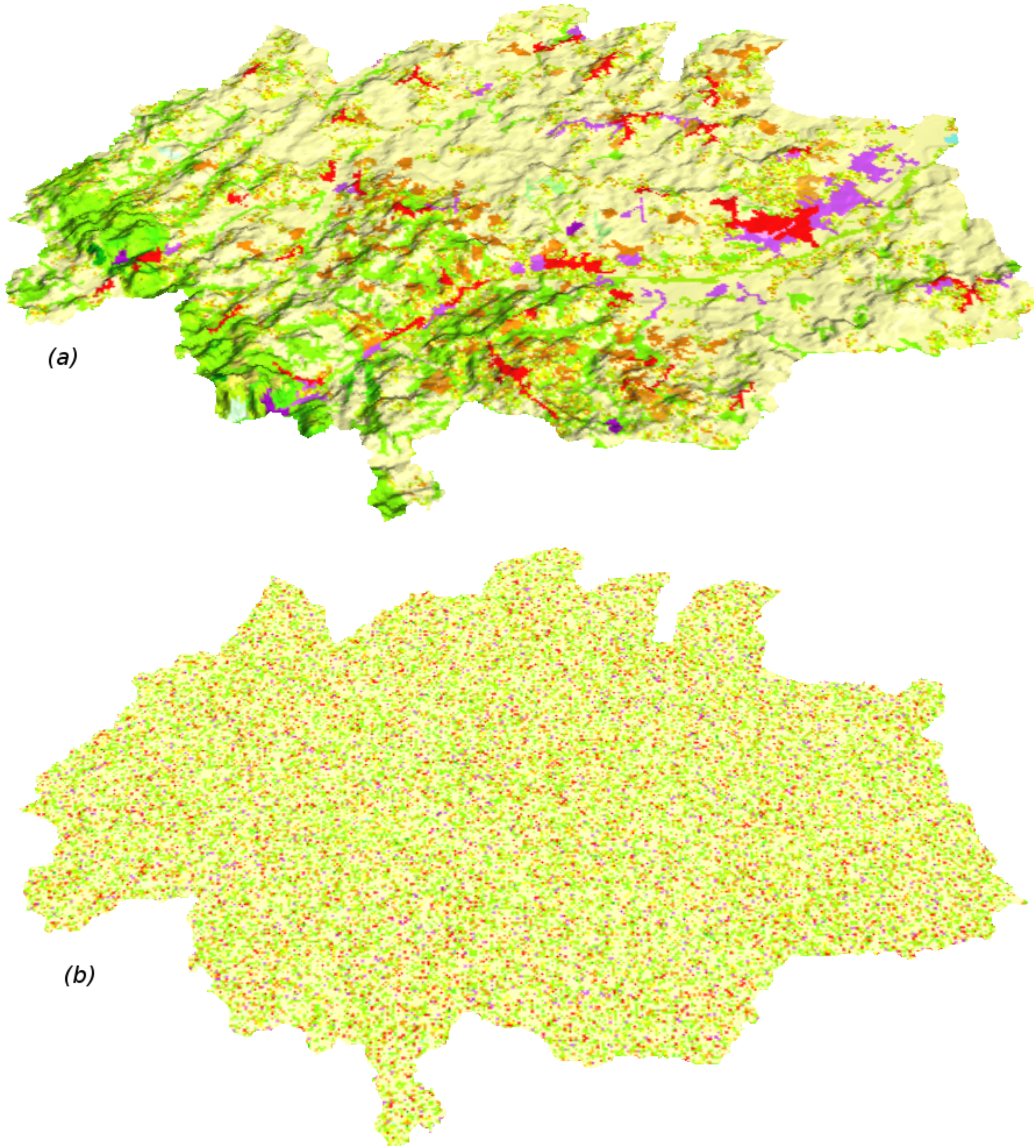
- alignment of Corine Land Cover dataset with Census datasets (reclassification);[18]

- initial farmer spatial allocation and land allocation (as described in section 2.3.2);

- random object's vintage at the beginning of simulation;

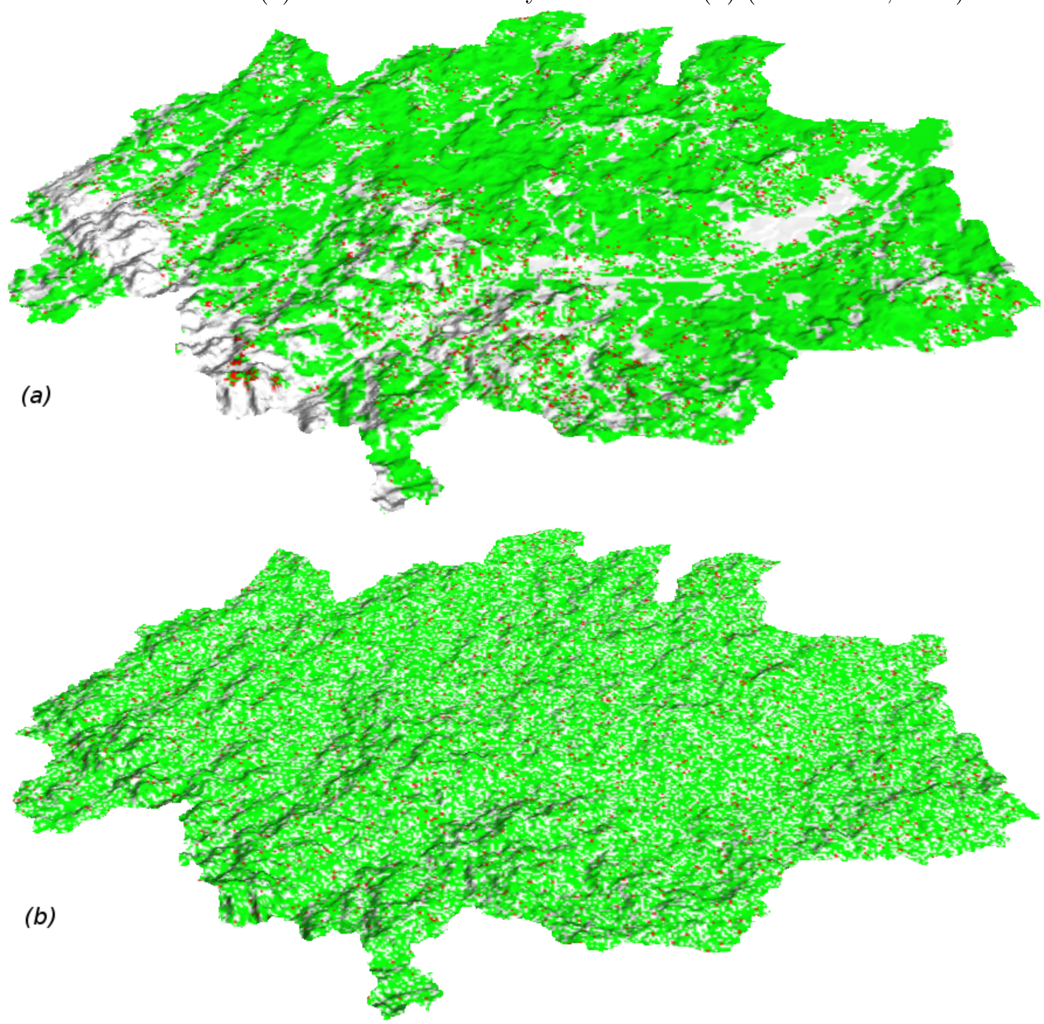
[18]Corine Land Cover map includes some mixed classes whose plots are randomly reallocated to specific categories obtaining aggregated values that are consistent with census statistics.

Figure 5: Land use classes and DTM in the real RegMAS simulation area (a) and in the randomly shuffled case (b)



Map colours refer to the standard Corine Land Cover legend, downloadable from http://dataservice.eea.europa.eu

Figure 6: Agricultural land use (in green) versus land abandonment (in red) in the RegMAS simulation area (a) and in the randomly shuffled case (b) (*hc* scenario, 2015)



- random rental contracts' duration;

- sequence of free plots' entrance in the bidding process.

RegMAS takes advantage of modern programming languages allowing the random number generator "seed" to be either re-initialised at each run or kept fixed. If the seed remains fixed, simulations reproduce exactly the same output given the same input and, consequently, differences across scenarios' simulations can be only attributed to the different inputs (i.e., policy measures). Still, results depend on a particular, though fixed between scenarios, random extraction.

Therefore, we repeat simulations 5 times, any time changing the random seed in order to assess the robustness of results or, in other words, to assess to what extent the stochastic components of the model affect simulation results. Table 6 reports average (avg.), standard error (st. err.) and coefficient of variation (cv) for the main model aggregate results over the 5 repetitions. Results are evidently very stable across repetitions but, though very low, the coefficient of variation strongly depends on the size of the experiment, that is, of the area under study. In particular, Table 6 indicates that in smaller regions both border effects and the smaller set of agents (farmers) lead to a higher variability over the stochastic components.[19] This evidence represents an argument in favour of applying RegMAS to larger regions as this implies more robust results in simulation analysis. Larger regions, however, also brings about a higher computational burden. This trade-off between robust-

[19]Here "border effects" indicate the effects on agent's behaviour of being close to the borders of the simulation area. Spatial simulations can avoid border effects using periodic boundary conditions (e.g. running the simulation on a toroidal surface) or can reduce them using a larger region.

ness and computational costs is actually minimised in RegMAS compared to other simulation toolkits. Castella et al. (2005), for instance, use the Cormas Toolkit (Bousquet et al., 1998) to perform simulations on a relatively small (50x50) grid,[20] thus implying much lower computational burden but lower robustness, as well. Nonetheless, even in RegMAS the optimal compromise between these two aspects, and, therefore, the optimal regional size for application, is still to be found and deserves further attention in future research.

Table 6: Results robustness: results of 5 simulation repetitions with different random number seed, *hc* scenario in 2015)

	full region (48,679 ha UAA)			sub-region (931 ha UAA)		
	avg.	st. err.	cv	avg.	st. err.	cv
number of farms (n)	4,294	11.9	0.0028	87	2.8	0.0320
avg. size (UAA ha/farm)	10.98	0.0	0.0027	10.7	0.4	0.0410
exiting farms (n)	1,430	11.9	0.0083	23	2.8	0.1196
abandoned land (%)	3.31	0.0	0.0139	0.8	0.2	0.2187
farm profit (euros/farm)	11,340	55.3	0.0049	12,834	353.1	0.0275
- *including CAP aids (euros/farm)*	16,148	53.5	0.0033	17,394	274.7	0.0158
income (euros/farm)	20,929	48.3	0.0023	20,762	63.9	0.0031
off-farm labour (h/farm)	956	9.4	0.0098	392	59.0	0.1505
total agr. labour (AWU)	2,928	26.4	0.0090	87	4.0	0.0465

5. Concluding remarks

This paper presents and tests RegMAS, an open-source, spatially explicit agent based modelling framework (and software), designed to assess the possible impact of alternative scenarios (mainly changes in policy regime) on

[20]In comparison, the present simulations are ran on a 396x301 grid, with 69,143 non-zero cells.

heterogeneous farm structures, income and land use. The main original feature of RegMAS rests on the fact that it allows agents (farmers) to take into account spatially-explicit information in formulating their behaviours and, thus, it allows assessing the consequent economic (as well as environmental) outcome at both the micro (plot-by-plot) and the macro (aggregate) levels.

By assessing its functioning on a portion of a central Italian region (Marche) and under two alternative CAP scenarios (the 2003 Reform and the Health Check), our simulation demonstrates the advantages of such spatial explicitness. Results suggest that the model behaves as expected in all major aspects and, thus, it can be used to derive the aggregate response of a complex and heterogeneous system whenever the external environment (and, in particular, the policy regime) is exogenously modified. Furthermore, by making the spatial dimension explicit, RegMAS seems more able, compared to conventional ABMs, to associate these macro results to the underlying micro (land use) behaviours such as lent renting, land abandonment, and exiting the business.

As the major purpose of the paper is to provide an original contribution on explicit spatial modelling within conventional (spaceless) ABMs, simulation results specifically emphasize the interesting insights concerning the often disregarded effects of transport costs and loss of margins due to altitude which allow such kind of models to generate more plausible results on how external changes (policy reform, in the present case) impact agricultural activity.

Though here applied to specific policy measures, RegMAS is flexible enough to allow adaptation over a large set of different scenarios (change in agricultural prices, introduction of environmental regulations, introduction of new technologies, etc.). This more extensive application can be one possible direction of further research on this modelling tool. Further effort is also needed to assess the optimal geographical size of model application and in improving its original features especially concerning how space affects land market, transport costs, performance and agents' interaction. Eventually, as on open-source software, RegMAS can be further developed in these or other directions by user themselves.

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